ORIGINAL ARTICLE

The Use of Machine Learning to Support the Diagnosis of Oral Alterations

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ABSTRACT

Objective: To verify the accuracy of deep learning models in detecting cellular alterations in histological images of oral mucosa. **Material and Methods:** The study compares three convolutional neural network (CNN) architectures for classifying histological images: EfficientNet-B3, MobileNet-V2, and VGG16. Efficient and focused on computer vision, each has specific advantages. A Kaggle database with 5192 images was used, divided into training (70%), validation (15%), and test (15%) sets. The CNNs were implemented using the Keras library, trained with pre-trained ImageNet weights, and evaluated using accuracy and AUC metrics. **Results:** The findings indicate that EfficientNet-B3 achieved the lowest training and validation losses at epoch 30, with the highest accuracy and stability during training. Evaluation metrics showed EfficientNet-B3 with 98% accuracy and 99% sensitivity for oral squamous cell carcinoma (OSCC) images, outperforming MobileNet-V2 and VGG16. MobileNet-V2 achieved 97% accuracy and 96% sensitivity, while VGG16 reached 94% accuracy and 93% sensitivity for OSCC images. All models exhibited high sensitivity and specificity in differentiating between normal and OSCC images, as demonstrated by ROC curves. EfficientNet-B3 had the highest AUC (0.982), followed by MobileNet-V2 (AUC=0.967) and VGG16 (AUC=0.937). These findings underscore the effectiveness of EfficientNet-B3 for accurately detecting cellular alterations in histological images of oral mucosa. **Conclusion:** Our study reveals the superior performance of CNNs, particularly EfficientNet-B3, in classifying histological images of OSCC.

Keywords: Deep Learning; Mouth Neoplasms; Neural Networks, Computer; Machine Learning.

Introduction

Oral cancer is a common disease all over the world, mainly affecting men over the age of 50. According to studies, it accounts for around 3% of all cancer cases diagnosed globally [1-3]. The most common type of oral cancer is squamous cell carcinoma (OSCC), accounting for around 90% of all diagnosed cases. This neoplasm originates in the squamous cells lining the mouth and can spread to adjacent tissues and other parts of the body, such as the lymph nodes and lungs [3,4]. The incidence of mouth cancer varies between different regions of the world and is more frequent in countries with risky cultural and behavioral habits, such as tobacco and alcohol consumption, exposure to the sun and a nutrient-poor diet, as well as exposure to the HPV virus [5]. There are also reports in the literature of a higher risk of mouth cancer associated with socioeconomic status [6]. The survival rate for oral squamous cell carcinoma is 80% for localized cases and less than 50% for advanced cases. Sequelae include problems with speech, swallowing, chewing, and quality of life [7,8]. Prevention and early detection of oral cancer are fundamental to guaranteeing survival and quality of life for patients [2,3].

There are various techniques for diagnosing OSCC, including clinical examination, biopsy and imaging tests, with biopsy being considered the gold standard, allowing histological analysis of the tissue [9]. However, it is possible to highlight some difficulties related to performing the biopsy. One of these difficulties is inter-observer variability in the histopathological interpretation of biopsy specimens, which can lead to misdiagnoses and delays in treatment [10]. Another difficulty is the possibility of the tumor being understaged in the biopsy, which can lead to inadequate treatment [2].

In recent years, the use of Artificial Intelligence (AI) has gained prominence in oral cancer research, especially in diagnostic and prognostic aid. AI has shown potential for improving the early detection of oral cancer, increasing the effectiveness of diagnosis and reducing the time patients have to wait for accurate results. In addition, AI has been used to predict the prognosis of mouth cancer patients, identifying those with a higher risk of disease recurrence and allowing more aggressive therapeutic measures to be taken early on [11,12].

The use of machine learning techniques has proved to be a promising tool for the diagnosis and prognosis of OSCC. The results described in the literature suggest that these techniques can be used as a complementary approach to conventional diagnostic and prognostic methods, improving the accuracy and speed of the process [13-15]. However, there is much progress to be made in the knowledge and application of AI resources for diagnostic aid in health, understanding which algorithms are most appropriate and their accuracy. The use of convolutional neural network (CNN) algorithms has shown promise for classification in this context. An example is the use of deep learning to diagnose oral changes from histopathological images [16]. A challenge that remains in this area is the high computational requirements [17] and the diversity of existing algorithms [16], which can mean a greater delay in using AI for diagnostic support. Therefore, one of the gaps that this study aims to explore is the comparison of the performance of three CNN algorithms, two of them more widely used (MobileNet and VGG) and a lightweight one - EfficientNet, which has been poorly tested in its B3 version for the detection of OSCC in histological images, allowing the use in clinical context to be facilitated by selecting the one with the best performance. Therefore, the aim of this study was to verify the accuracy of deep learning models in detecting cellular alterations in histological images of oral mucosa.

Material and Methods

Study Design and Architectures Used

This is a cross-sectional study comparing deep convolutional neural network (CNN) models for classifying histological images. Three convolutional neural network architectures were used: EfficientNet-B3,

MobileNet-V2 and VGG16, all of which are focused on computer vision tasks. EfficientNet models are built on the concept of composite scalability. They use an optimization strategy that seeks to efficiently scale the depth, width and resolution of the network. This allows the models to achieve competitive performance in various computer vision tasks, even with computational constraints, with the EfficientNet-B3 model being a specific member of this family, which was designed to achieve a balance between performance and computational efficiency [18]. The MobileNet-V2 architecture uses a combination of techniques, such as separable convolution layers, linear activation per layer, inverted residuals and linear expansion. These techniques are applied to achieve a more efficient architecture in terms of memory consumption and computing power, while maintaining competitive performance in computer vision tasks [19]. The VGG16 model was proposed in 2015 and stands out for its deep structure and the use of convolutional layers with small filters (3x3) and max pooling (2x2). According to Simonyan and Zisserman [20], the choice to use smaller filters in all layers of the network allows for greater depth and a better representation of image characteristics, while maximum pooling helps to reduce dimensionality and extract the most relevant characteristics.

Database and Image Preparation

The database was obtained from the Kaggle website (www.kaggle.com), which is an open-access community for data science, on November 30, 2023. The database used is called "Histopathologic Oral Cancer Detection using CNNs", which contains histological images of oral epithelium, classified dichotomously as images without disease and images of patients with squamous cell carcinoma. The images were obtained using magnifications of 100x and 400x with a resolution of 96 dpi, JPG format with three color channels (RGB). They were resized in order to be used as input for the Machine Learning model, and they were adjusted to 224x224 pixels in order to match the expected input for the CNN models.

All 5192 images in the database were used in the analyses. The images were already classified in the database and reviewed by the same investigator to verify the presence of cellular changes. Of these, 2698 (52%) were with disease, and 2494 (48%) were without disease (Figure 1). The dataset was randomly divided using random sampling from the Scikit-Learn Library [21] into three categories: (1) training set (70%; n = 3634 images); (2) validation set (15%; n = 779 images); and (3) test set (15%; n = 779 images). Figure 2 shows some images from the data set.
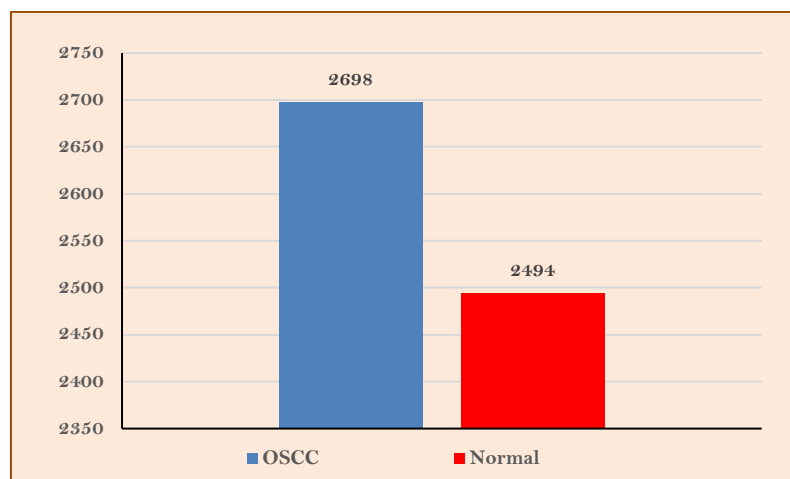

Figure 1. Distribution of images according to OSCC and normal classification.
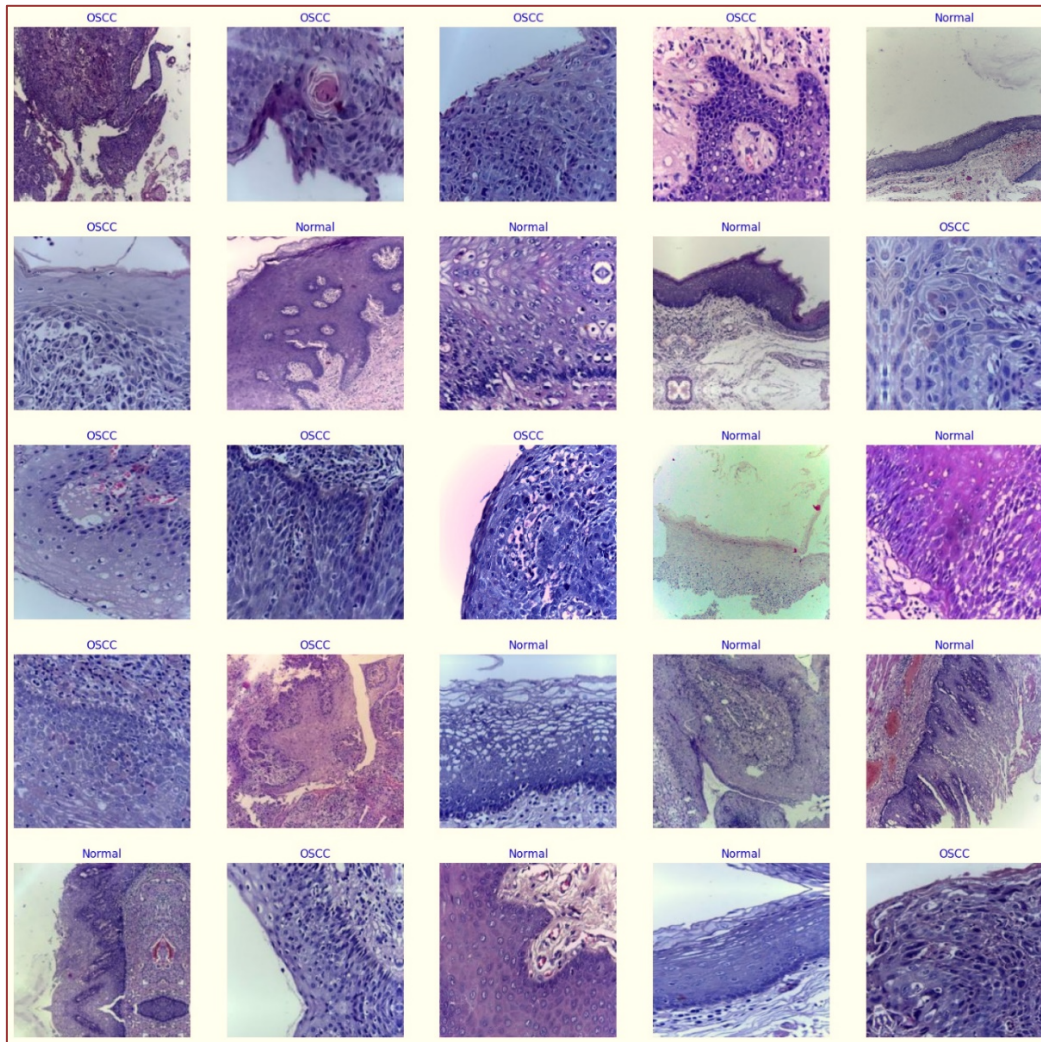
Figure 2. Sample images from the dataset at different magnifications.

Development and Implementation of Convolutional Neural Networks

The CNN model was built using five sequential layers: (1) an input layer with convolutional and pooling layers transferred from the proposed architecture (EfficientNet-B3, MobileNet-V2 and VGG16), expected image size of 224 x 224 x 3; (2) a batch normalization layer; (3) a dense layer with a rectified linear unit (ReLU) activation function; (4) a Dropout layer with a rate of 0.45; and (5) an output layer with a Softmax activation function.

The proposed models were implemented using the Keras library (keras.io). The Adam optimizer was used to train the models with a learning rate of 0.001 and a batch size of 32 [22]. All the parameters of the convolutional and clustering layers of the architectures used were initialized using the pre-trained weights from ImageNet [23]. In order to reduce the dissimilarities between the predicted and actual probability distributions, the "categorical cross-entropy" loss function was used.

Two callbacks were used during the training process. The first callback was "EarlyStopping", used to monitor validation loss and stop training if no improvement is observed (patience = 5 epochs), thus preventing overfitting. The second callback was "ReduceLROnPlateau", which reduces the learning rate when a metric stop improving (patience = 4 epochs), thus dealing with problems of stagnation in model learning (https://keras.io/api/callbacks/). All the analyses were carried out using the Google Colab environment (colab.research.google.com).

Model Evaluation Metrics

Two metrics were used to assess the model's performance: accuracy and area under the ROC curve (AUC). Accuracy is calculated by dividing the number of correct predictions by the total number of samples tested and is a general indicator of performance. The AUC metric is used to assess the model's performance in correctly classifying positive classes as positive and negative classes as negative. Both metrics were calculated using the Scikit-Learn library implementation [21]. Table 1 shows the learning models used in this study as well as their parameters (Table 1).

Table 1. Learning models used in this study.

CNN Model	Non-Trainable Parameters	Trainable Parameters	Total Parameters
EfficientNet-B3	90.375	11.093.290	11.183.665
MobileNet-V2	36.672	2.554.882	2.591.554
VGG-16	1.024	14.847.554	14.848.578

■ Results

During the training process, it was found that the lowest training and validation losses occurred at epoch 30 for EfficientNet-B3, epoch 29 for MobileNet-V2 and epoch 40 for VGG16 (Figure 3), with EfficientNet-B3 achieving the highest accuracy in the fewest epochs tested during training and accuracy validation and remaining more stable (Figure 4).
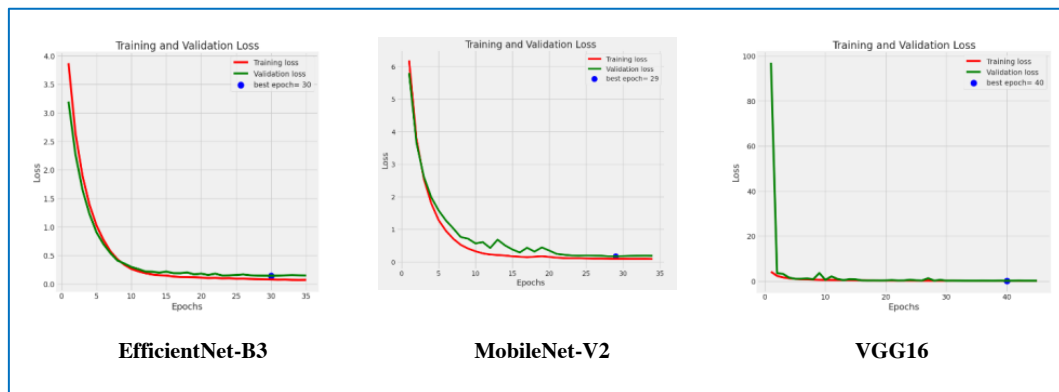

Figure 3. Training loss, Validation loss, and best training time according to models.
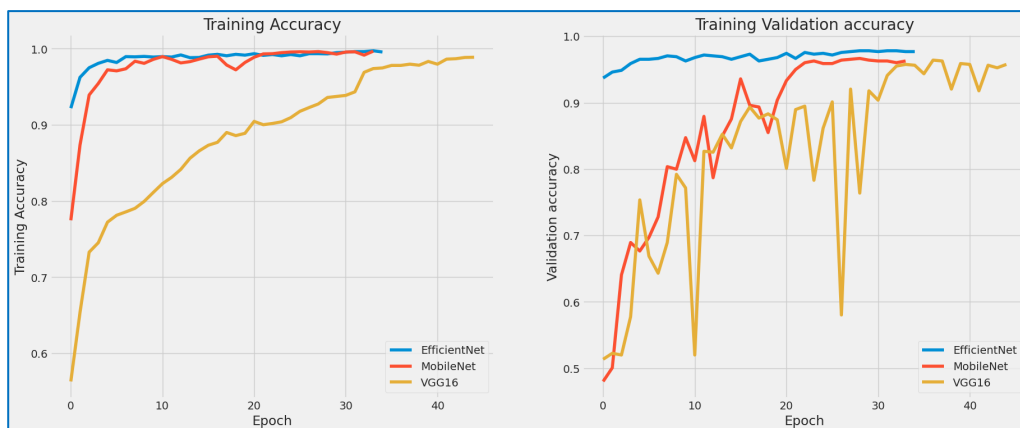

Figure 4. Comparison of the training process of the three different models.

The evaluation metrics for the EfficientNet-B3 learning transfer model showed 98% accuracy and 99% sensitivity for images with OSCC. MobileNet-V2 showed 97% accuracy and 96% sensitivity for images with OSCC. VGG16 obtained an accuracy of 94% and a sensitivity of 93% for images from the OSCC group (Table 2).

Table 2. Accuracy of the deep learning models tested in detecting cellular alterations in histological images of oral mucosa.

Variables	Categories	Precision	Recall (sensitivity)	f1-score	Accuracy
EfficientNet-B3	Unaltered images	0.99	0.98	0.98	0.98
	OSCC images	0.98	0.99	0.98	
MobilleNet-V2	Unaltered images	0.96	0.97	0.97	0.97
	OSCC images	0.97	0.96	0.97	
VGG16	Unaltered images	0.93	0.94	0.94	0.94
	OSCC images	0.95	0.93	0.94	

The ROC (receiver operating characteristic) curve showed that all the models tested had high sensitivity and specificity in differentiating images with normal characteristics from those with OSCC (Figure 5). The highest cut-off point was for EfficientNet-B3 (AUC=0.982), followed by MobileNet (AUC=0.967) and VGG16 (AUC=0.937).
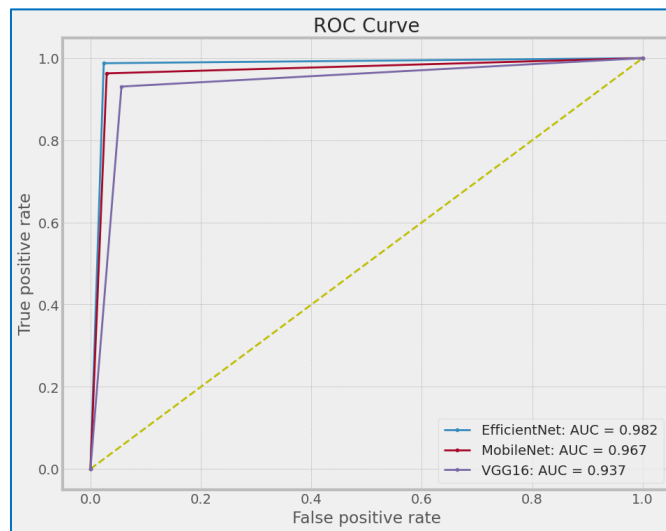

Figure 5. ROC (receiver operating characteristic) curve for the different models tested.

■ Discussion

The results of this study have shown that the three CNN transfer learning models tested have a high diagnostic potential, all of which have an accuracy of over 93% in the architectures used. Of particular note is the EfficientNet-B3 architecture, which achieved 98% accuracy in image classification.

The use of AI has grown substantially in the health sector, helping to reduce diagnostic errors [14]. While pathologists have the ability to interpret and analyze the complex characteristics present in histological samples, taking into account the clinical context and their experience, AI models, especially those based on CNNs, have shown remarkable performance in classifying histological images, achieving results comparable to and, in some cases, superior to pathologists. AI can identify subtle patterns and features imperceptible to the human eye, offering an objective and consistent analysis. However, the expertise and knowledge of pathologists

are still fundamental to clinical interpretation and decision-making in complex cases. The combination of human skills and AI can lead to more accurate diagnoses and improvements in patient care by decreasing intra- and inter-observer variability [24]. This high performance can be confirmed by this study, as all deep learning models showed good accuracy in classifying histological images of oral cancer, which can be an excellent alternative to help pathologists detect patterns and guide early intervention as quickly as possible.

Early detection of cellular alterations in oral cancer is extremely important for effective diagnosis and treatment. Through the early identification of precancerous or cancerous lesions, it is possible to intervene at the early stages of the disease, significantly improving survival rates and reducing associated morbidity [25]. In this context, the EfficientNet-B3 architecture demonstrated superior metrics compared to the other algorithms tested (98% accuracy). Compared to other existing CNN architectures, EfficientNet plays a promising role using advanced deep-learning techniques for accurate image classification. Its architecture combines scalability, depth, width, variable kernel size and resource optimization to extract relevant features from histological images, enabling the automated detection of abnormal cellular changes [18,26]. On the other hand, MobileNet-V2 is known for its lightness and speed, and also demonstrated a good capacity to correctly classify the images in this study (97% accuracy). It uses the convolution separation technique to reduce computational cost by splitting convolutions into two stages: a spatially separable convolution and a depth convolution. This results in an architecture that is efficient in terms of computational resources, while maintaining a good feature extraction capacity [19]. Although it may have a slightly lower performance compared to EfficientNet-B3, MobileNet-V2 can still be a viable option for detecting cellular changes in oral cancer in scenarios with computational resource constraints. VGG16, on the other hand, is an older but widely used and well-established CNN architecture. It stands out for its depth and ability to learn discriminative features (Table 1). However, this architecture is heavier in terms of computational resources and has a significant number of parameters [20]. Although it can provide accurate results in detecting cellular alterations in oral cancer, VGG16 may be less efficient in terms of training time and inference when compared to the other two architectures mentioned.

All the models used demonstrated excellent sensitivity and specificity metrics for classifying images, comparable to traditional pathological analyses. However, even with these results, a systematic review of the literature pointed out that it is still difficult to incorporate this technology into clinical practice and that it needs to be simplified so that it can be translated into platforms that are easy for professionals to use [11].

In a study comparing the use of deep learning to identify OSCC with the diagnostic accuracy of pathologists, it was possible to identify that CNN collaborated with the increase in caution of professionals during the classification of images, when they were assisted by the model, reducing the number of images classified as false positive and reducing the time for classification [14]. In this same study, the 7-layer convolutional CNN model obtained greater diagnostic accuracy than the pathologists [14].

An advantage of this study is the large number of images in the database compared to previously published work [27,28]. This feature provides greater variability in the analysis, reducing the risk of classification bias [28]. Similarly, the use of a cloud environment for analysis, such as Google Colab, with limited computational capacity, brings the results closer to real-world application. On the other hand, this feature also poses a challenge for the modeling, since the scarcity of computational resources directly affects the adjustment of some parameters, such as the batch size [17]. Another challenge related to the use of CNNs is the possibility of overfitting, which often does not allow such high accuracy in situations other than the one in which the model was trained. Another limitation of this study is the difficulty of interpreting deep learning models. Although they are powerful in their predictions, the difficulty in understanding how the models make their decisions should be

the subject of future research. It is also suggested that other versions of the EfficientNet model, with greater scalability of parameters, be tested in new studies evaluating their efficiency in classifying histopathological images of oral lesions.

Therefore, some challenges need to be overcome in order to use AI in healthcare. These include the use of CNN architectures for the classification of mouth cancer staging, applying multiclass models and contributing to clinical decision-making. There is also a need to incorporate AI into the day-to-day practices of clinicians, thus contributing to speed and assertiveness in diagnosis, especially in areas with less access to qualified human resources, increasing the population's access to early diagnosis and treatment. Further research in this area is needed to incorporate these models into clinical practice, as well as the integration of these models into devices to assist professionals, which tends to increase the diagnostic capacity of oral cancer, especially in the early stages.

■ Conclusion

All the deep learning models used in this study demonstrated a high capacity to correctly classify histological images with cellular alterations of squamous cell carcinoma. The model with the best performance among those tested was EfficientNet-B3, followed by MobileNet-V2 and then VGG16. Therefore, the routine use of AI to aid in the diagnosis of oral cancer is very promising.

■ Authors' Contributions

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All authors declare that they contributed to critical review of intellectual content and approval of the final version to be published.

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■ Conflict of Interest

The authors declare no conflicts of interest.

■ Data Availability

The data used to support the findings of this study can be made available upon request to the corresponding author.

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